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Impact of Artificial Intelligence on Educational Development in Nigeria

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Abstract

Several real-world studies have shown that artificial intelligence (AI) can improve learning outcomes. This is because AI is technologically advanced. However, developing countries like Nigeria have not fully adopted the AI system in their schools because most government tertiary institutions in Nigeria do not have AI technologies. So, the point of this study is to look into how AI tools like smart tutoring, blockchain technology, adaptive learning, plagiarism detection, and predictive analytics have affected educational development in Nigeria, adding something new to what is already known. The quantitative survey research design was adopted in this study by administering a structured questionnaire to the government tertiary institutions in Nigeria. An outline of the demographic data was made using descriptive statistics. Recentred influence functions (RIF) regression was used to look into how AI tools affect educational development. The Pearson correlation was used to determine how strong and in what direction the link is between AI and educational development in Nigeria. The RIF regression indicates that the AI tools have a positive significant impact on educational development, suggesting that an increase in the AI tools contributes to the betterment of Nigeria's educational development while the Pearson correlation illustrates a moderate positive link among the AI tools and educational development. Thus, the Nigerian government needs to make sustainable policies that will allow higher education institutions to use AI more effectively, which will lead to better learning outcomes and enhance educational development in the country.

Keywords: Artificial intelligence, Educational Development, RIF-regression, Pearson Correlation.

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Introduction

The swift progression of artificial intelligence (AI) has transformed the worldwide educational framework, presenting novel methods to improve teaching, learning, and administrative functions. Worldwide, AI instruments including adaptive learning platforms, intelligent tutoring systems, and plagiarism detection technologies have become essential for promoting personalized and effective education (Zawacki-Richter et al., 2019). These technologies allow instructors to customize instructional strategies to address the distinct requirements of learners, foster collaborative learning, and enhance educational results. AI-driven adaptive learning platforms evaluate individual learning behaviors' and deliver tailored information to accommodate varying cognitive abilities (Strielkowski *et al*., 2024). Likewise, plagiarism detection systems have bolstered academic integrity, guaranteeing the legitimacy of scholarly work (Ogwueleka, 2025).

In industrialized nations, the use of AI into educational frameworks has markedly enhanced learning experiences and results. Governments in these countries have allocated resources to AI research and application to promote inclusive and accessible education for everyone (Holmes, 2019). Nonetheless, the circumstances in developing countries, especially in Nigeria, are markedly distinct. Nigeria's expanding tertiary education system has significant constraints in AI adoption due to infrastructure deficiencies, insufficient finance, and a shortage of qualified experts to oversee AI technology (Okunade, 2024). Education is important to Nigeria's socio-economic advancement, since it provides individuals with the information and skills necessary to succeed in a competitive global market. The Nigerian education sector has persistently faced systemic issues, including overcrowded classrooms, insufficient teaching resources, and inconsistent curriculum (Angwaomaodoko, 2023). These challenges impede the provision of excellent education, placing the nation at a disadvantage in international educational rankings. Incorporating AI into the national educational system may alleviate these issues by enhancing efficiency, diminishing administrative costs, and augmenting learning results.

Blockchain technology, a component of AI, may be employed to securely and transparently maintain student data, therefore resolving problems related to human record-keeping and credential verification (Strielkowski *et al*., 2024). Intelligent tutoring systems may mitigate teacher shortages by offering students immediate support, especially in science, technology, engineering, and mathematics (STEM) disciplines. Predictive analytics can identify at-risk students, enabling institutions to intervene promptly and offer tailored assistance (Holmes, 2019). Nonetheless, the potential of AI to revolutionize Nigeria's education system remains predominantly unexploited. Although commercial universities have begun to investigate AI-powered technologies, the majority of government-owned tertiary institutions are deficient in the necessary infrastructure and money for adoption (Okunade, 2024). This difference illustrates a wider issue of unequal access to technical resources, which intensifies educational inequality across institutions.

The integration of AI into Nigeria's educational framework is also hindered by socio-cultural influences and opposition to technological advancement. A multitude of stakeholders, including educators, policymakers, and students, express skepticism about the relevance and applicability of AI inside the local setting. Furthermore, there exists a paucity of empirical research about the influence of AI on educational advancement in Nigeria, complicating the formulation of evidence-based policies and interventions (Ogunleye, 2019). This study seeks to address this gap by examining the impact of certain AI tools—smart tutoring, blockchain technology, adaptive learning, plagiarism detection, and predictive analytics on educational development in Nigeria.

The primary aim of this study is to examine the impact of various technological innovations on educational development with the following specific research objectives; to assess the impact of smart tutoring on educational development, examine the role of blockchain technology in enhancing educational development, evaluate how adaptive learning technologies influence educational development, investigate the contribution of plagiarism detection systems to educational development, and determine the effect of predictive analytics on educational development.

Materials and Methods

Research Design

This study adopts a survey research design utilizing a quantitative approach to investigate the impact of artificial intelligence (AI) tools on educational development in Nigeria. The quantitative approach allows for the collection and analysis of numerical data, providing objective insights into the relationship between AI tools and their influence on educational development. Structured questionnaires were used to gather primary data from respondents within government tertiary institutions across Nigeria. This design is suitable because it ensures statistical representation and facilitates the application of inferential analysis to draw conclusions about the population based on the sample.

Sampling technique and Sample Size Determination

The study employed a purposive sampling technique to focus specifically on both government and private tertiary institutions within the Southwest geopolitical zone of Nigeria. Purposive sampling is justified because it allows the study to target institutions where AI adoption or potential for adoption is most relevant to the research objectives. To determine the sample size, the Cochran (1963) is applied as follows:

$$n = \frac{Z^2 \times p \times (1-p)}{E^2}$$

n = sample size

Z = Z-value (from standard normal distribution, For a 95% confidence level, Z=1.96)

p = estimated proportion of the population (0.5),

E = margin of error (0.05)

$$n = \frac{1.96^2 \times 0.5 \times (1-0.5)}{0.05^2}$$

$$n = \frac{3.8416 \times 0.25}{0.0025}$$

$$n = 384$$

Analytical Method

Recentered Influence Functions (RIF) regression: rifhdreg

The model employed in this study can be illustrated as follow:

RIF $\{y, v(F_y)\} = X'\beta + \varepsilon_i$, then, $E(\varepsilon_i) = 0$

According to Rios-Avila (2020a), Rifhdreg is an extension of RIFs (Recentered influence functions) with robustness against outliers and provides a simple framework for analyzing the impact of changes in the distribution of X's on distribution statistics at margin which can be used to fit a linear model to capture how small changes in the distribution of the independent variables X affect $v(F_y)$ and therefore has slight changes in the interpretation of the coefficient which is different from Ordinary Least Squares (OLS) regression.

Meanwhile, $v(F_y)$ is the response variables which is the educational development while X's is the small changes in the distribution of the independent variables identified as the AI tools like smart tutoring, blockchain technology, adaptive learning, plagiarism detection, and predictive analytics and the β is the coefficient estimate of X's while the ε_i is the stochastic error term. Similarly, the same model estimation is estimated with the response variable as educational development and the independent variables as the smart tutoring, blockchain technology, adaptive learning, plagiarism detection, and predictive analytics. Causal inference is facilitated through the utilization of the Rifhdreg model (Rios-Avila, 2020b), which computes the effect of alterations in smart tutoring, blockchain technology, adaptive learning, plagiarism detection, and predictive analytics utilization on educational development. The Rifhdreg model is appropriate for analyzing complex relationships in real-world data due to its resistance to outliers and deviations from normality. The Rifhdreg model was selected due to its capacity to offer valuable insights regarding the causal connection that exists among smart tutoring, blockchain technology, adaptive learning, plagiarism detection, predictive analytics and educational development in Nigeria. Rifhdreg, in contrast to conventional regression models, provides robustness against outliers and deviations from normality, rendering it well-suited for examining the intricate and multifaceted effects of AI tools like smart tutoring, blockchain technology, adaptive learning, plagiarism detection and predictive analytics on educational development (Ramzan et al., 2023).

However, the reliability of the construct items using Cronbach Alpha was carried out and Alpha was determined to be 0.961 indicating that there is a high level of internal consistency, suggesting that the research instruments and questionnaire are good. The 5-likert scale of the variables are ordinal scales which are converted to composite scales of continuous scale measurement to enable the use of quantitative methods like RIF-regression and Pearson correlation. The skewness and Kurtosis tests were also adopted to validate the reliability of the continuous scale data while normality of the RIF-model residuals and multicollinearity tests were also carried out to ascertain the validity of the RIF-model.

Results

Table 1 presents the demographic information of the study's respondents. The majority of respondents were male (52.1%), followed by females (44.3%), while 3.6% preferred not to disclose their gender. In terms of age, the largest proportion (39.1%) fell within the 25–34 years age group, with a smaller distribution across other groups, including 20.8% under 25 years, 23.4% aged 35–44 years, 10.4% aged 45–54 years, and 6.3% aged 55 years and above. Regarding the type of institution, 41.7% were affiliated with federal government tertiary institutions, 36.5% with state government tertiary institutions, and 21.9% with private tertiary institutions. Most respondents (46.9%) identified as academic staff, while administrative staff accounted for 31.3% and IT personnel made up 21.9%. The years of experience varied, with the majority having over 15 years of experience (36.5%), followed by 31.3% with 5–10 years, 21.9% with 11–15 years, and 10.4% with less than 5 years.

Table 1: Demographic Information

Variables	Choices	Frequency	Percentage (%)
Gender	Male	200	52.1
	Female	170	44.3
	Prefer not to say	14	3.6
Age Group	Under 25 years	80	20.8
	25–34 years	150	39.1
	35–44 years	90	23.4
	45–54 years	40	10.4
	55 years and above	24	6.3
Institution Type	Federal Government Tertiary	160	41.7
	State Government Tertiary	140	36.5
	Private Tertiary Institution	84	21.9
Role in Institution	Academic Staff	180	46.9
	Administrative Staff	120	31.3
	IT Personnel	84	21.9
Years of Experience	Less than 5 years	40	10.4
	5–10 years	120	31.3
	11–15 years	84	21.9
	Over 15 years	140	36.5

Table 2 provides the summary statistics for the key variables under investigation. The mean values for all variables are fairly consistent, ranging between 3.46 and 3.51, indicating a moderate to high level of agreement among respondents regarding the influence of these variables on educational development. The standard deviations (SD), which range from 0.53 for educational development to 0.88 for the other variables, suggest that responses were relatively clustered around the mean, reflecting a consistent perception among respondents. Median values across the variables also align closely with the means, further reinforcing the central tendency of the data. The range, which varies from 2.95 to 3, highlights a relatively narrow spread of responses, indicating uniformity in participants' assessments. Besides, the reliability of the continuous scale version of the AI tools including the smart tutoring, blockchain technology, adaptive learning, plagiarism detection, predictive analytics and educational development was validated with their corresponding skewness approaching zero and kurtosis approaching 3, indicating that the dataset is normally distributed, validating the reliability of the continuous scale version of the dataset.

Table 2: Summary Statistics

Variables	Mean	Sd	Median	Range	Skewness	Kurtosis
Smart Tutoring	3.46	0.88	3.53	2.95	0.002	2.756
Blockchain Technology	3.51	0.88	3.5	2.97	0.038	2.749
Adaptive Learning	3.5	0.88	3.5	2.98	0.004	2.748
Plagiarism Detection	3.51	0.88	3.53	2.98	-0.059	2.794
Predictive Analytics	3.51	0.87	3.55	2.97	-0.024	2.788
Educational Development	3.48	0.53	3.5	3	-0.104	2.907

Table 3 presents the correlation matrix for the relationships among smart tutoring, blockchain technology, adaptive learning, plagiarism detection, predictive analytics, and educational development. Notably, educational development exhibits positive correlations with all the independent variables, with coefficients ranging from 0.3350 (adaptive learning) to 0.4881 (smart tutoring). These correlations suggest that smart tutoring has the strongest positive association with educational development, followed closely by plagiarism detection (0.4529) and blockchain technology (0.4407). Predictive analytics also shows a moderate positive correlation (0.4225), while adaptive learning contributes a slightly weaker but still meaningful positive correlation. The correlations among the independent variables themselves are generally weak, with some near-zero or negative values, indicating absence of multicollinearity and a distinct contribution of each variable to educational development.

Table 3: Correlation Matrix

Variables	Smart Tutoring	Blockchain Technology	Adaptive Learning	Plagiarism Detection	Predictive Analytics	Educational Development
Smart Tutoring	1					
Blockchain Technology	0.0321	1				
Adaptive Learning	-0.1174	0.0136	1			
Plagiarism Detection	-0.0237	-0.0262	0.0242	1		
Predictive Analytics	-0.0075	-0.0283	-0.0083	0.0274	1	
Educational Development	0.4881	0.4407	0.3350	0.4529	0.4225	1

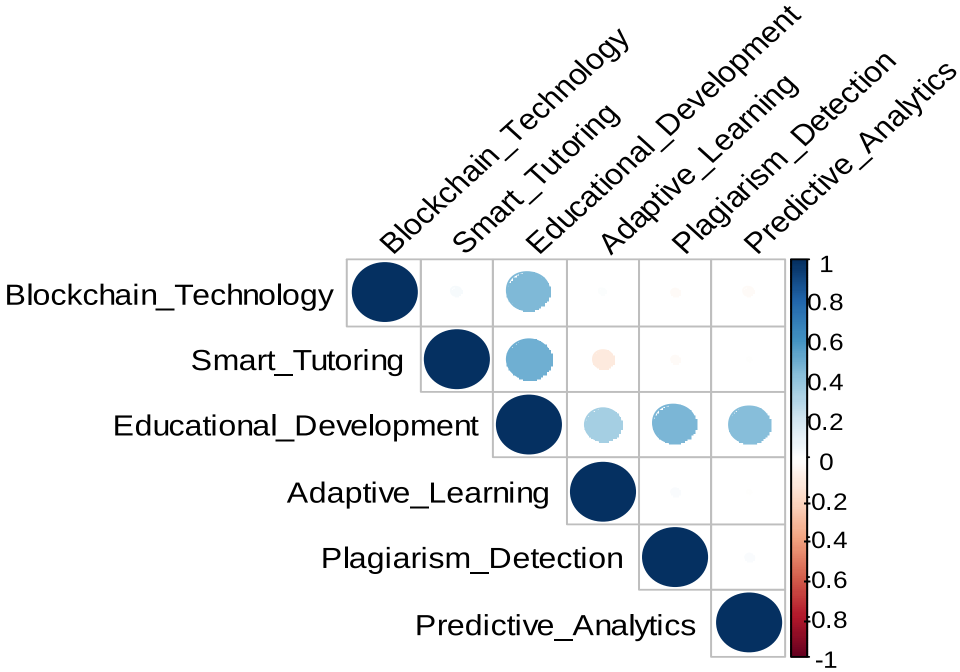

Figure 1: Correlation Plot

Figure 1 ascertain the degree or strength of relationship between the variables under study visually.

Table 4 presents the RIF-regression model's overall p-value which is less than 0.05 significant level, indicating that educational development is significantly related to tools such as smart tutoring, blockchain technology, adaptive learning, plagiarism detection, and predictive analytics. The estimated coefficient of the RIF regression shows that tools like smart tutoring, blockchain technology, adaptive learning, plagiarism detection, and predictive analytics have probability values less than 0.05 significant level, rejecting the null hypothesis and implying that they are statistically significant at a 5% level and have a positive significant impact on the educational level, suggesting that increase in the AI-tools will contribute to better educational development in Nigeria. This supported the research hypotheses H1, H2, H3, H4 and H5 respectively. The R-squared value of 0.9719 and R-squared adjusted of 0.9715 indicates that over 97% variation in educational development can be attributed to AI tools like smart tutoring, blockchain technology, adaptive learning, plagiarism detection, and predictive analytics. The variance inflation factor (VIF) of all the predictor variables (AI tools) is less than 5, indicating that the fitted VIF-regression model does not occur the problem of multicollinearity and model residuals probability value of 0.111 exceeds 0.05 significant level, indicating that the model residuals are normally distributed. This suggests that the fitted RIF-regression model is adequate.

Table 4: RIF-Regression showing the impact of AI-tools on educational development

Overall Model P-value = 0.000, R-squared = 0.9719, Normality (P-value) = 0.111

Educational Development	**Coefficient**	**Robust Error**	**Standard**	**P-value**	**VIF**
Smart Tutoring	0.321	0.005		0.000	1.02
Blockchain Technology	0.266	0.005		0.000	1.00
Adaptive Learning	0.231	0.005		0.000	1.01
Plagiarism Detection	0.275	0.005		0.000	1.00
Predictive Analytics	0.262	0.005		0.000	1.00
Constant	-1.259	0.041		0.000	NA

Discussion

The findings from the analysis provide valuable perception into the effect of smart tutoring, blockchain technology, adaptive learning, plagiarism detection and predictive analytics on educational development. The demographic information revealed a fairly balanced representation in terms of gender, age groups, and institutional roles, providing a diverse sample to explore the study variables. The predominance of participants from federal and state government tertiary institutions suggests a broad institutional coverage, strengthening the generalizability of the results within the education sector. The summary statistics indicate that all independent variables—smart tutoring, blockchain technology, adaptive learning, plagiarism detection, and predictive analytics—have similar mean scores (ranging from 3.46 to 3.51) and moderate variability (standard deviations around 0.88), signifying that respondent generally perceived these technologies as moderately impactful on educational development. Educational development, the dependent variable, had the lowest variability (SD = 0.53), reflecting a consistent perception of its importance among respondents. The high range values for all variables suggest diverse opinions within the sample, further enriching the findings.

The correlation matrix shows significant positive relationships between educational development and all the independent variables. The strongest correlations were observed with smart tutoring (r = 0.4881) and plagiarism detection (r = 0.4529), suggesting these variables play critical roles in advancing educational development. Blockchain technology, predictive analytics, and adaptive learning also exhibited moderate positive correlations, emphasizing their supportive roles in enhancing the education sector. These findings suggest a synergistic relationship among the variables, where integrating these technologies could holistically improve educational outcomes. The RIF-regression analysis provides deeper insights into the varying impacts of the predictors across different quantiles of educational development. The RIF-regression indicates that the AI tools including the smart tutoring, blockchain technology, adaptive learning, plagiarism detection, and predictive analytics have positive significant impact on the education development, indicating that increase in the AI tools enhance the educational development in Nigeria. This also align with the research hypotheses H1 to H5. This finding also aligns with the work of Okunade, (2024); Rashid et al., (2021); and Adetayo & Ogunleye (2022) suggests that while these technologies are essential, their effectiveness depend on the specific educational context or developmental stage.

Conclusion and Policy Implication

In conclusion, this study explored the impact of emerging technologies—smart tutoring, blockchain technology, adaptive learning, plagiarism detection, and predictive analytics—on educational development. The findings indicate that these technologies play significant and complementary roles in enhancing the quality, efficiency, and accessibility of education. The findings illustrated that AI-tools such as smart tutoring, blockchain technology, adaptive learning, plagiarism detection, and predictive analytics have a positive significant impact on educational development, suggesting that an increase in AI tools will enhance Nigeria's educational development while the Pearson correlation illustrates a moderate positive link among the AI tools and educational development. Thus, the Nigerian government needs to make sustainable policies that will allow higher education institutions to use AI more effectively, which will lead to better learning outcomes and enhance educational development in the country.

Base on the result of findings, the policy implication are as follows:

i. Governments and educational institutions should prioritize funding for the development and deployment of smart tutoring systems, as they have the highest positive impact on educational development. This investment can address learning gaps and improve student outcomes through personalized instruction.
ii. Policymakers should encourage the adoption of blockchain technology to enhance transparency in academic record-keeping, certification processes, and intellectual property protection, fostering trust and reducing fraud in educational systems.
iii. Educational stakeholders should promote the use of adaptive learning technologies to cater to diverse student needs, ensuring personalized learning experiences that can accommodate different skill levels and learning styles.
iv. The findings highlight the importance of plagiarism detection systems. Policymakers should enforce regulations mandating their use across institutions to uphold academic integrity and deter unethical practices.
v. Educational institutions should adopt predictive tools to forecast trends, optimize resource allocation, and monitor student progress.
vi. Policies should focus on training educators to effectively integrate and utilize these tools in their teaching methodologies.

References

Adebayo, S. O. and Oluwole, T. K. (2020). Barriers to the adoption of artificial intelligence in education: Evidence from Nigeria. *Journal of Educational Technology Research*, 12(3): 215–230.

Adetayo, A. B. and Ogunleye, O. A. (2022). Leveraging predictive analytics for improving student outcomes in Nigerian higher education. *African Journal of Educational Technology*, 15(2): 145–162.

Aljohani, N. R., Aldhafiri, T. M., & Alghamdi, M. F. (2021). Predictive analytics in higher education: Applications and challenges. *Journal of Educational Data Mining*, 13(1): 12–27.

Angwaomaodoko, E. A. (2023). A Comparative Study of Education Systems in Nigeria and Other Developing Countries. *Available at SSRN 4853871*.

Arroyo, I., Woolf, B. P., Burelson, W., Muldner, K., Rai, D., & Tai, M. (2014). A multimedia adaptive tutoring system for mathematics that addresses cognition, metacognition and affect. *International Journal of Artificial Intelligence in Education*, 24: 387-426.

Dwivedi, Y. K., Hughes, D. L., & Ismagilova, E. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. *International Journal of Information Management*, 57: 102261. https://doi.org/10.1016/j.ijinfomgt.2020.102261

Ewa, M. A. (2023). Artificial Intelligence (AI) Literacy: An Investment for Enhancing Educators' Skills in AI-Powered Primary Schools in Nigeria. *International Journal of Education and Development using Information and Communication Technology*, 19(1): 45–60.

Holmes, W. (2019). Artificial intelligence in education: Promises and implications for teaching and learning. *Center for Curriculum Redesign*.

Knewton. (2018). *Personalized Learning with Adaptive Learning Technologies*. Retrieved from https://www.knewton.com

Ogunleye, B. O. (2019). Some determinants of visibility boost for research publications among early career educational researchers in Southwest, Nigeria. *African Journal of Pedagogy*, 8(1): 93-111.

Ogunode, N. J., Abigeal, I. and Lydia, A. E. (2021). Education and underdevelopment in Nigeria: Causes and implications. *International Journal of Academic Research in Business and Social Sciences*, 11(1): 138–149.

Ogwueleka, F. N. (2025). Plagiarism Detection in the Age of Artificial Intelligence: Current Technologies and Future Directions. *AI and Ethics, Academic Integrity and the Future of Quality Assurance in Higher Education*, 10.

Okeke, C. O. and Eme, O. I. (2020). The challenges of educational development in Nigeria: Policy implications and prospects. *Journal of Education Policy and Practice*, 11(4): 87–100.

Okunade, A. I. (2024). The role of artificial intelligence in teaching of science education in secondary schools in Nigeria. *European Journal of Computer Science and Information Technology*, 12(1): 57-67.

Ramzan, M., Javaid, Z. K. and Fatima, M. (2023). Empowering ESL Students: Harnessing the Potential of Social Media to Enhance Academic Motivation in Higher Education. *Global Digital & Print Media Review*, 6(2): 224-237. https://doi.org/10.31703/gdpmr.2023(VI-II).15

Rashid, A., Ibrahim, S. and Yusuf, K. (2021). Plagiarism detection software and its implications for academic integrity: A case study of Nigerian universities. *Journal of Academic Ethics*, 19(1): 45–61.

Rios-Avila, F. (2020). Recentered influence functions (RIFs) in Stata: RIF regression and RIF decomposition. The Stata Journal, 20(1): 51-94. https://doi.org/10.1177/1536867X20909690

Siemens, G., Dawson, S., & Lynch, G. (2020). Improving the impact of learning analytics. *Journal of Learning Analytics*, 7(3): 25–39.

Strielkowski, W., Grebennikova, V., Lisovskiy, A., Rakhimova, G. and Vasileva, T. (2024). AI-driven adaptive learning for sustainable educational transformation. *Sustainable Development*, 33(2), 1921-1947.

UNESCO. (2021). Reimagining our futures together: A new social contract for education. Retrieved from https://www.unesco.org

Yu, Z. (2022). Sustaining student roles, digital literacy, learning achievements, and motivation in online learning environments during the COVID-19 pandemic. *Sustainability*, 14(8): 4388.

Zawacki-Richter, O., Marín, V. I., Bond, M. and Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators? *International Journal of Educational Technology in Higher Education*, 16(1): 1-27.